Deep Learning Based Massive MIMO Channel Acquisition

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Project Overview

Tasks:

Task#	Task Description
1■	Algorithm development for overhead reduction in massive MIMO channel acquisition
2■	Algorithm development for massive MIMO CSI feedback
3■	Algorithm development for joint overhead reduction and CSI feedback in massive MIMO systems

Project Milestones:

Task#	Planned Completion	Milestone (Deliverable)
1■	8/22	Task 1 Algorithm development
2■	11/22	Task 2 Algorithm development
3■	2/23	Task 3 Algorithm development
4■	10/23	Extensive simulation results in dynamic scenarios

Research Goals:

1. Develop efficient channel acquisition approaches for massive MIMO systems to reduce the associated training overhead.
2. Develop efficient channel feedback approaches for massive MIMO systems.
3. Extensive evaluation using accurate datasets.
4. Clear documentation of research, lessons learned and recommended approaches.

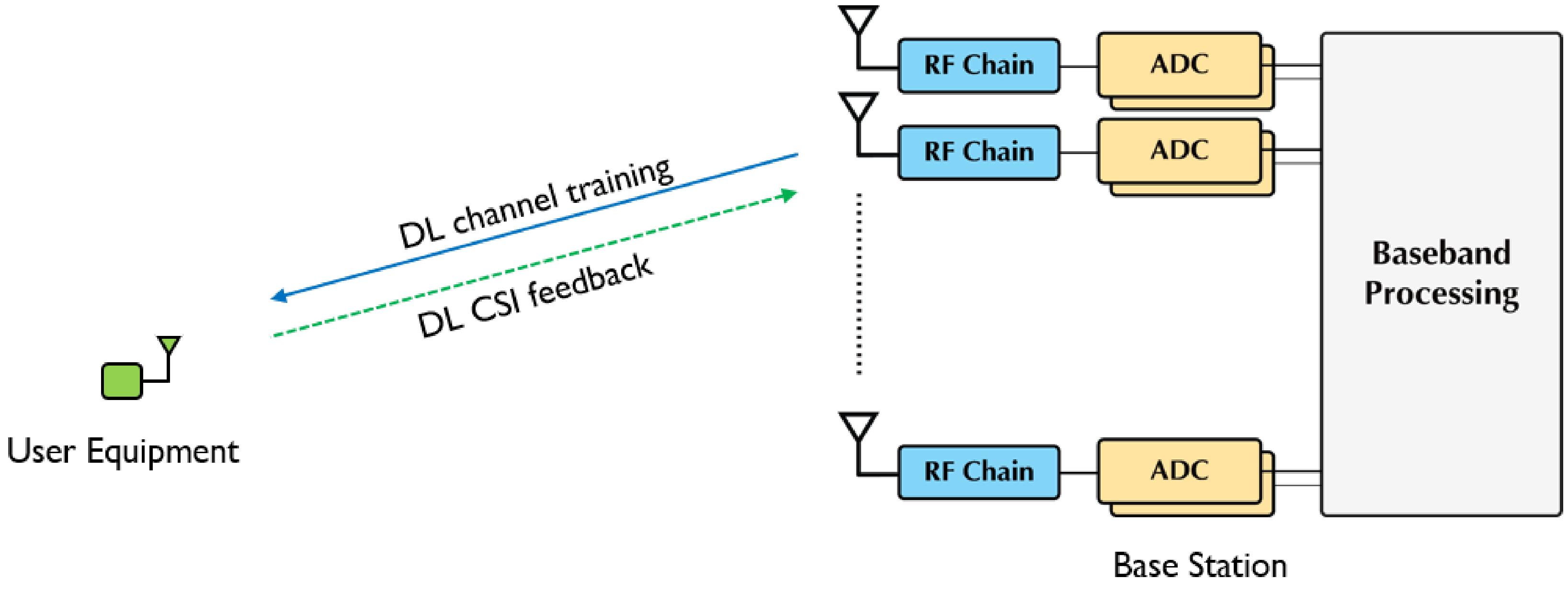
Benefits to Industry Partners:

1. Realizing the massive MIMO benefits in reality.
2. Algorithm toolbox for massive MIMO channel acquisition and feedback.
3. Accurate datasets for 5G/6G massive MIMO R&D.

[2] ■ Milestone complete or is on track for planned completion date
■ Milestone has changed from original sponsor-approved date (Why?)

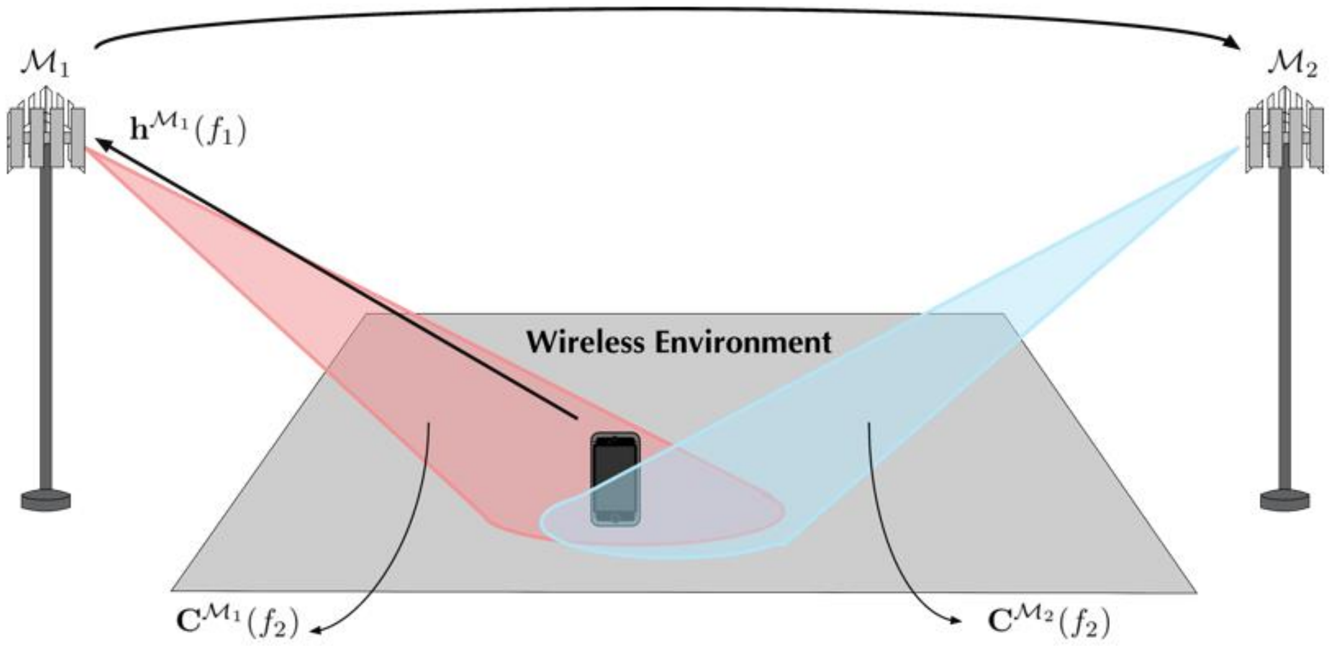
CSI acquisition in downlink FDD massive MIMO

- The challenges of acquiring CSI in DL FDD massive MIMO systems
  - Large **training** overhead: Large number of antennas
  - Large **feedback** overhead: High dimensional channel matrices (e.g., # Tx ant by # Rx ant by # Subband)



CSI acquisition in DL FDD massive MIMO systems requires large training and feedback overhead

Idea of statistical channel mapping



- Use ML to predict conditional downlink channel covariance given uplink channels
- Use classical channel training to estimate the final channel (requires a few pilots)

A practical approach that leverages deep learning for fast and robust channel prediction

Deep learning based downlink channel covariance prediction

$$\max_{f_\Theta(\tilde{\mathbf{h}}_{\mathrm{UL}})} \mathbb{P}\left(\hat{\mathbf{R}}_1 = \mathbf{R}_{s_1}, \ldots, \hat{\mathbf{R}}_U = \mathbf{R}_{s_U} | \tilde{\mathbf{h}}_{\mathrm{UL}_1}, \ldots, \tilde{\mathbf{h}}_{\mathrm{UL}_U}\right)$$

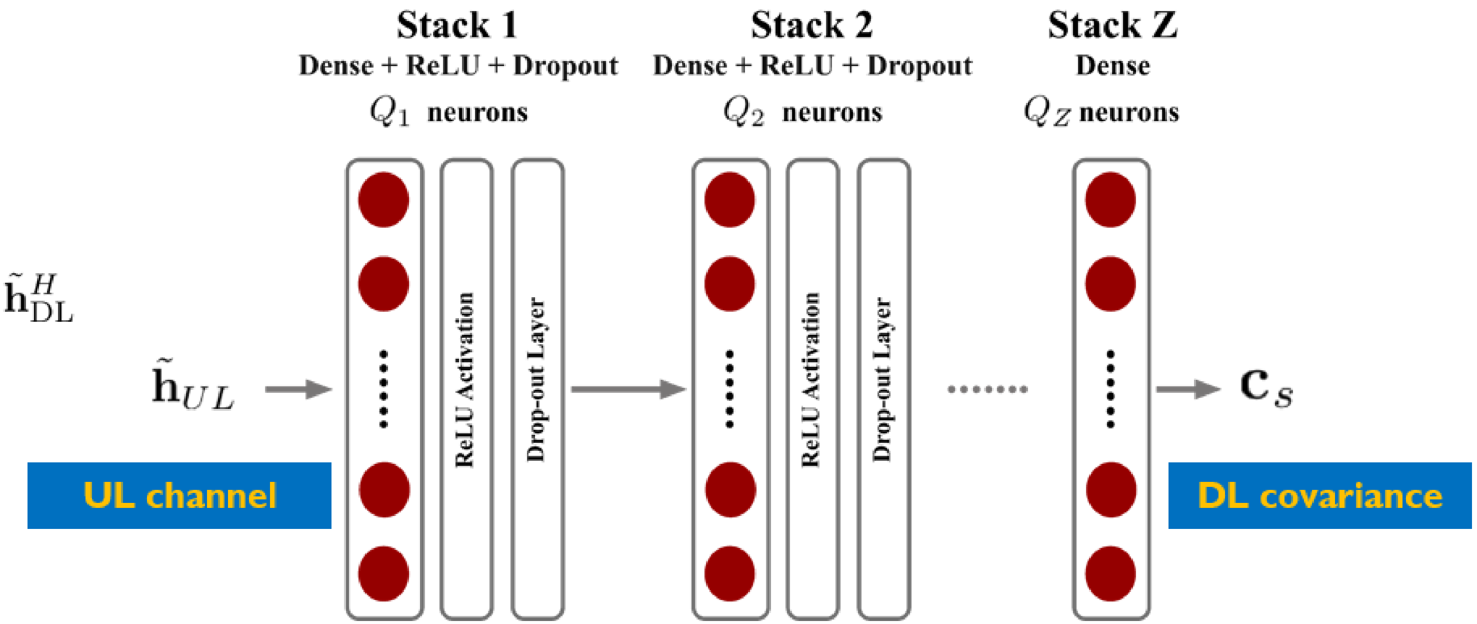
- Samples are i.i.d.
- Independent Gaussian noise
- $U \rightarrow \infty$

$$\mathbb{E}\left[\mathcal{L}\right] = \mathbb{E}\left[||\mathbf{R}_s - f_\Theta(\tilde{\mathbf{h}}_{\mathrm{UL}})||_F^2\right]$$

$$\mathcal{S} = \{(\tilde{\mathbf{h}}_{\mathrm{UL}}, \tilde{\mathbf{h}}_{\mathrm{DL}})\}_{u=1}^{U} \qquad \mathbf{R}_s = \tilde{\mathbf{h}}_{\mathrm{DL}} \tilde{\mathbf{h}}_{\mathrm{DL}}^H$$

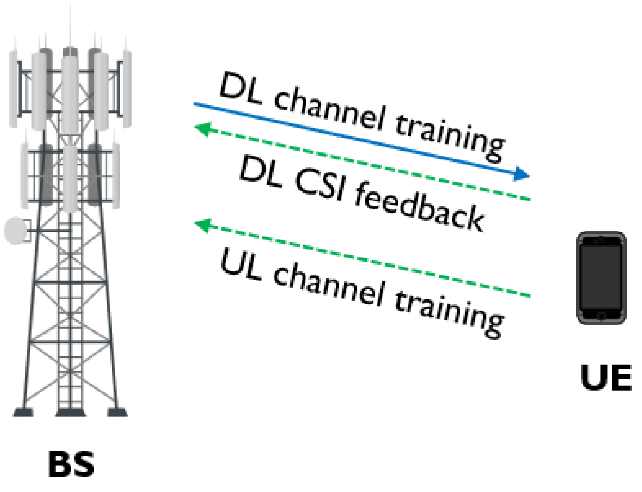
$$\mathcal{L} = \frac{1}{U} \sum_{u=1}^{U} ||\mathbf{r}_s - f_\Theta(\tilde{\mathbf{h}}_{in})||_2^2$$

- **Learning a conditional channel covariance predictor**
- **Mathematically proved optimality**
- **Well-fitted into the machine learning pipeline**



Practical operations

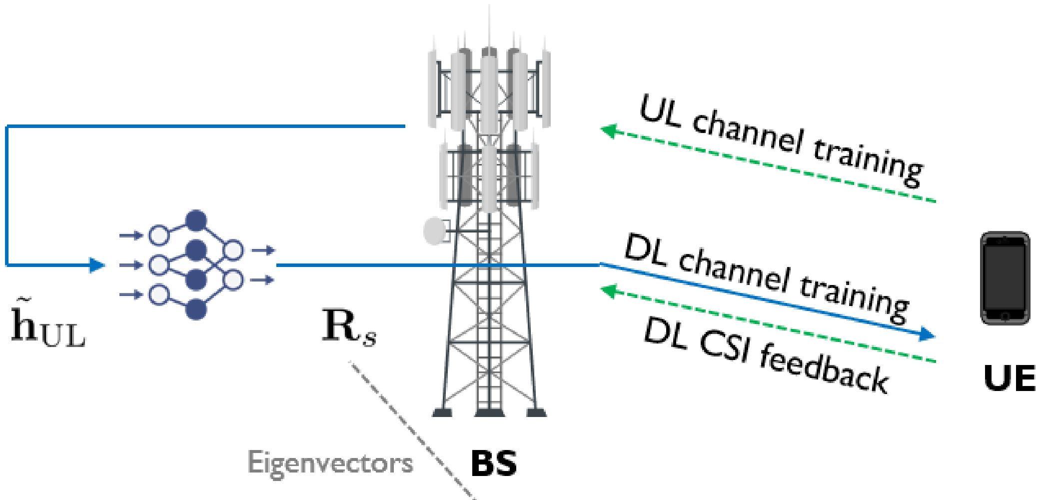
Training Phase



Dataset for training the deep learning model

$$\mathcal{S} = \{(\tilde{\mathbf{h}}_{\mathrm{UL}}, \tilde{\mathbf{h}}_{\mathrm{DL}})\}_{u=1}^{U}$$

Deployment Phase



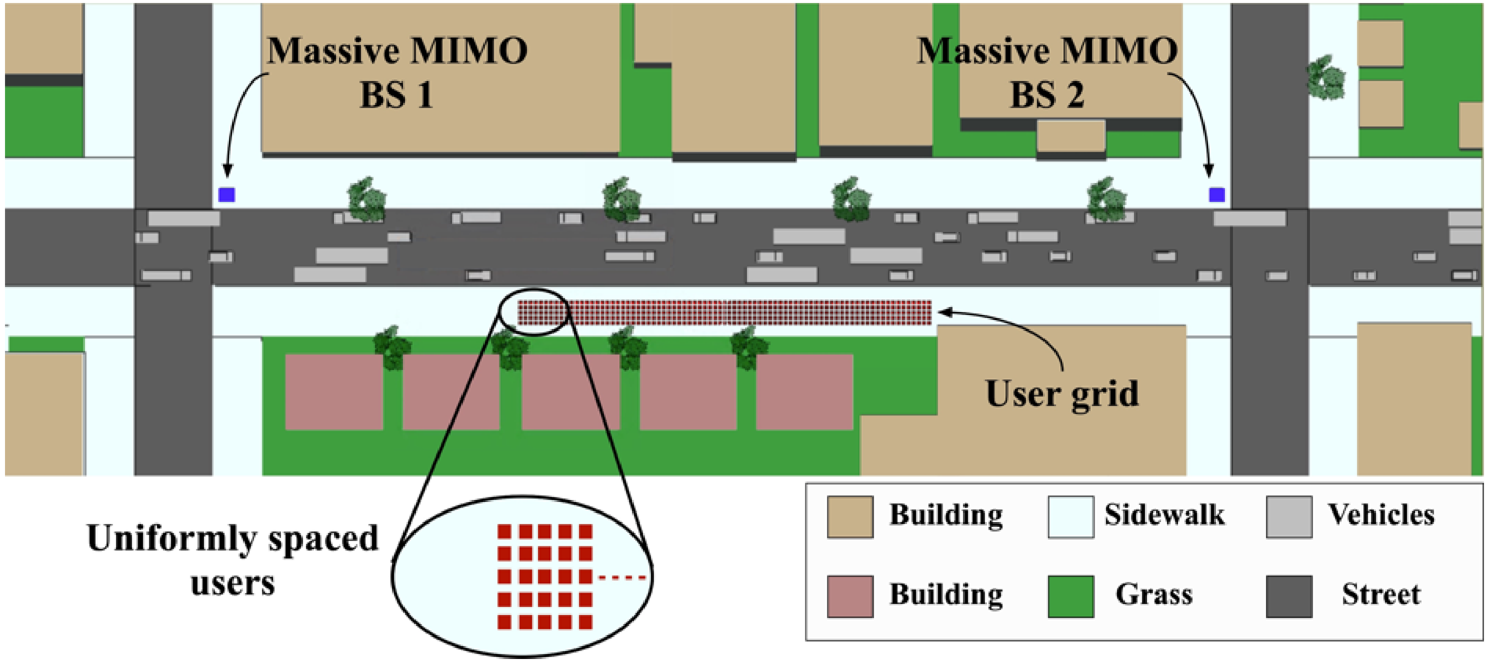
DL training direction

DL channel recon-
struction formula at BS

$$\widehat{\mathbf{h}}_{\mathrm{DL}} = \sum_{n=1}^{r} \left(\underbrace{\mathbf{u}_n^H \tilde{\mathbf{h}}_{\mathrm{DL}}}_{\text{CSI Feedback}} \right) \mathbf{u}_n$$

Reducing DL channel acquisition overhead by sending pilot signal along the most promising directions

Ray-tracing scenario



DeepMIMO Configuration

Hyper-parameter	Value
Scenario name	O1_dyn_3p4 O1_dyn_3p5
Active BS	1 and 2
Active users	Row 1-5
BS antenna array	(64, 1, 1)
Antenna spacing	0.5λ
Bandwidth	20 MHz
OFDM subcarrier	32
Number of multi-path	15

Simulation is conducted based on high-quality ray-tracing data that maintains spatial consistency

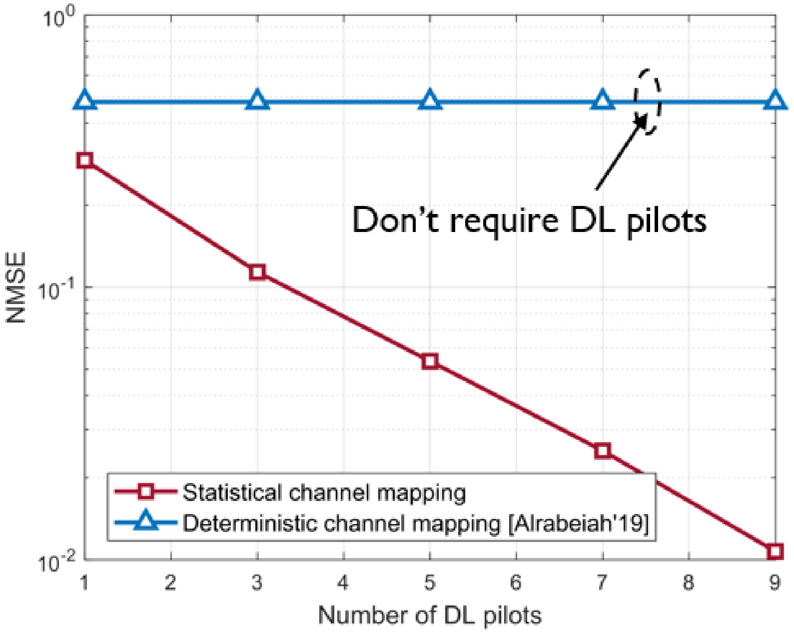
[DeepMIMO] A. Alkhateeb, "DeepMIMO: A generic deep learning dataset for millimeter wave and massive MIMO applications," Proc. of Information Theory and Applications Workshop (ITA), San Diego, CA, USA, 2019. URL: https://deepmimo.net/

Simulation results

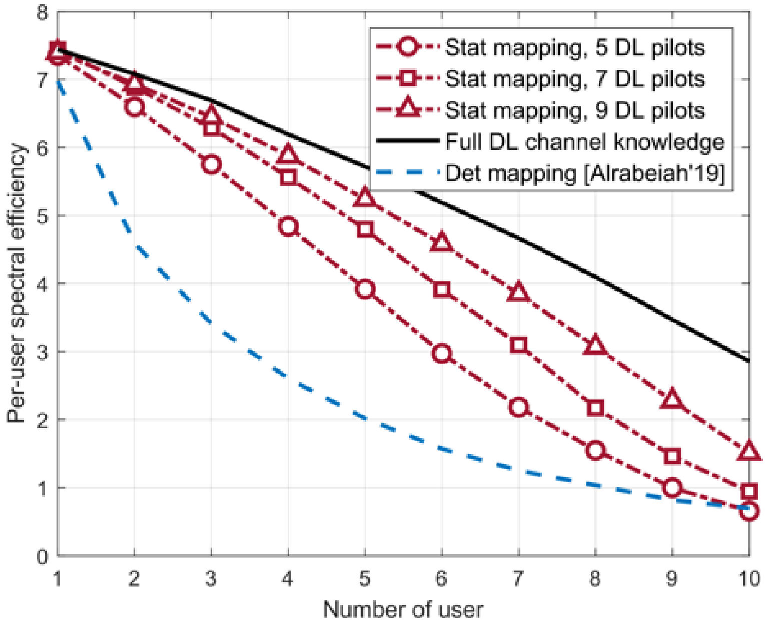
Simulation setup
BS antenna array: 64-ULA
UL frequency: 3.4 GHz
DL frequency: 3.5 GHz
Bandwidth: 20 MHz
Multi-path: 15

Training parameters
Solver: Adam
Learning rate: 0.001
Weight decay: 0
Batch size: 5,000
Number of epochs: 250
Learning rate decay: 0.1
Learning rate schedule: 20

Single-user channel estimation



Multi-user spectral efficiency



Statistical channel mapping achieves superior performance with only a few DL pilots

[Alrabeiah'19] M. Alrabeiah and A. Alkhateeb, "Deep Learning for TDD and FDD Massive MIMO: Mapping Channels in Space and Frequency," 2019 53rd Asilomar Conference on Signals, Systems, and Computers, 2019, pp. 1465-1470.